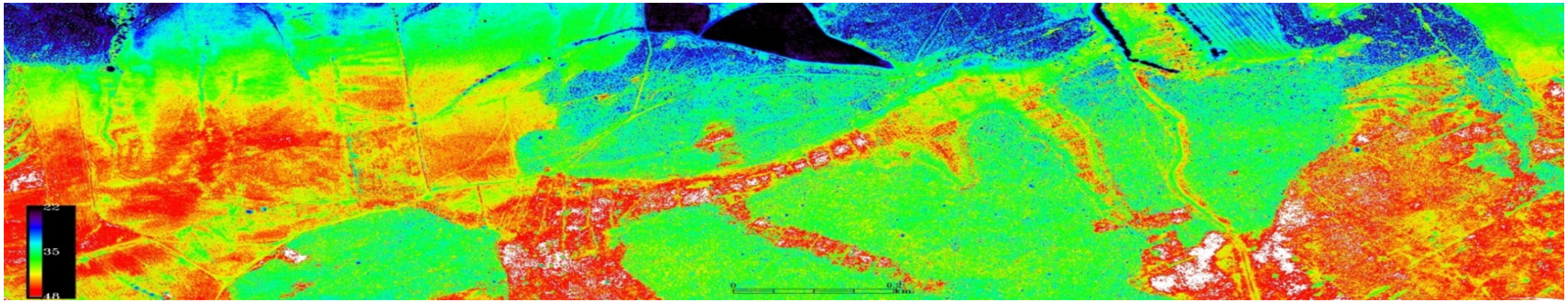
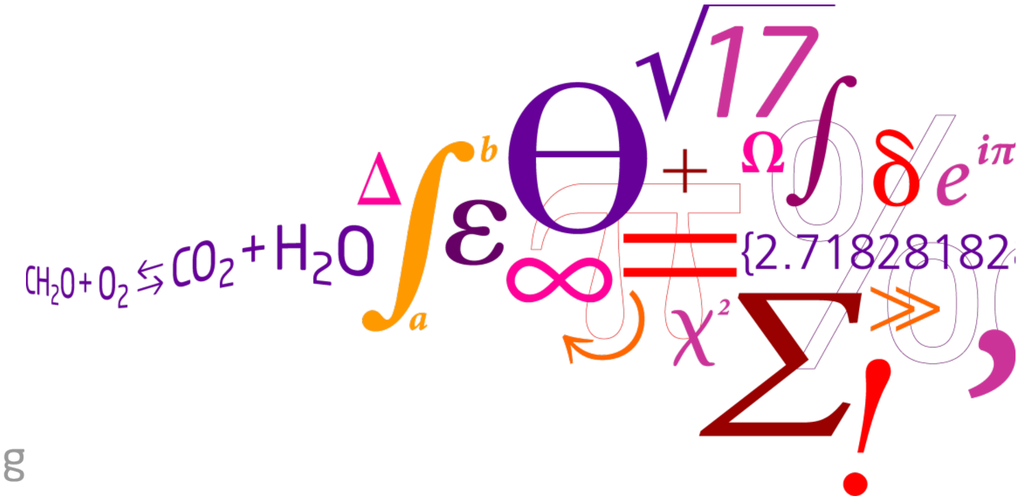


Water and carbon modeling of the land surface using remote sensing from Satellites and UAV

Monica Garcia

Assistant Professor

(coauthors at the end)



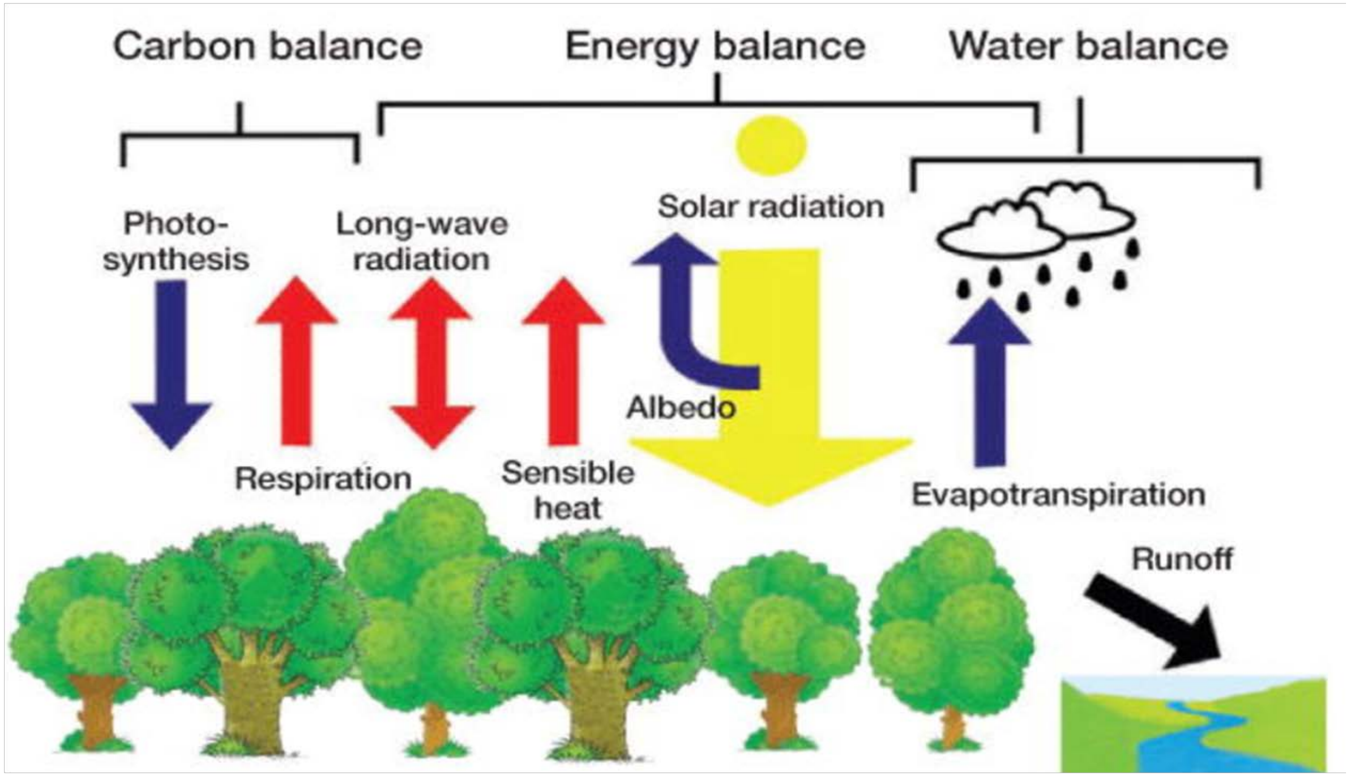
DTU Environment

Department of Environmental Engineering

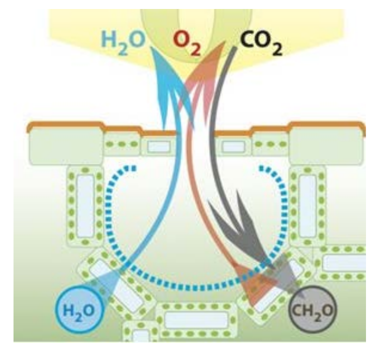
Warmer and extreme climate + Growing population

Impacts on water resources, food production and natural ecosystems

Flows of water and carbon between the land and the atmosphere are linked



Chapin et al., 2008



Uncertainty in our knowledge of water responses is directly dependent on uncertainty of carbon responses

Evapotranspiration (ET) estimates

❑ (traditional) water balance

$$\frac{dS}{dt} = P - ET - Q$$

P is rainfall, Q is runoff and dS change in storage

❑ (remote sensing) energy balance

$$Rn - G = H + \lambda ET$$

Rn is net radiation, *G* is soil heat flux, *H* is sensible heat flux and λET is latent heat flux (*ET* in energy units)

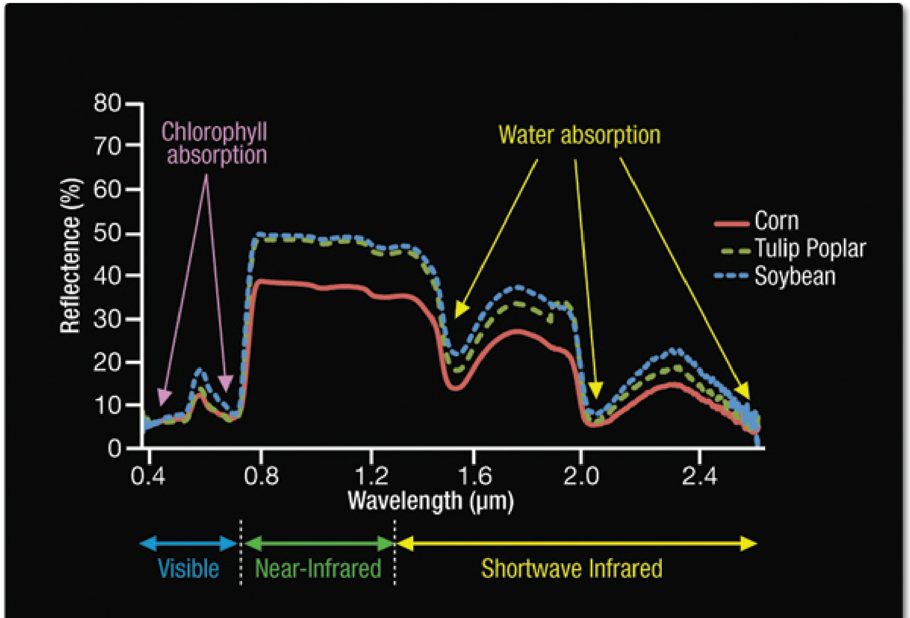
INPUT

- Meteorological data
- Land parameterization (soil depth, land cover type)

- **Radiometric Temp.**
- **Albedo**
- **Vegetation indices**
- Air temperature
- Radiation

Remote sensing: spectroscopy

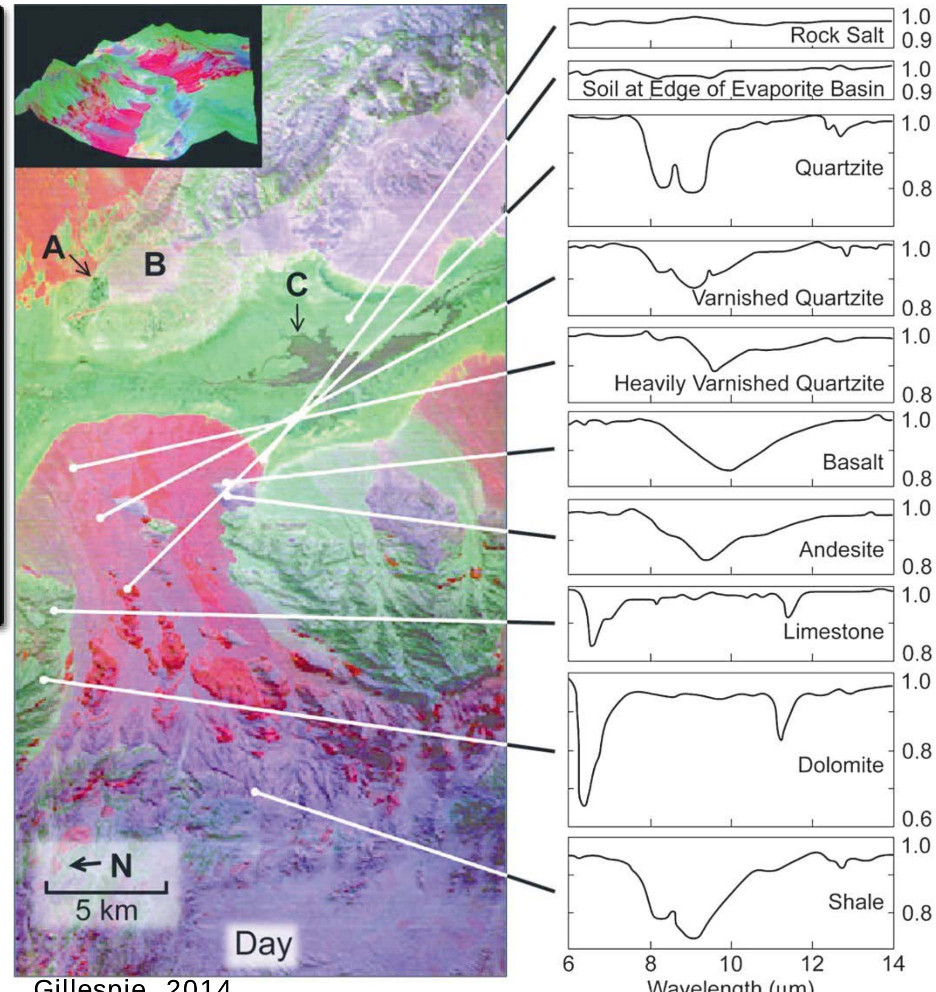
Solar range (0.4-2.4 μm)



Eric Brown de Colstoun

$$NDVI = \frac{(R_{800} - R_{670})}{(R_{800} + R_{670})}$$

Thermal range (5-12 μm)



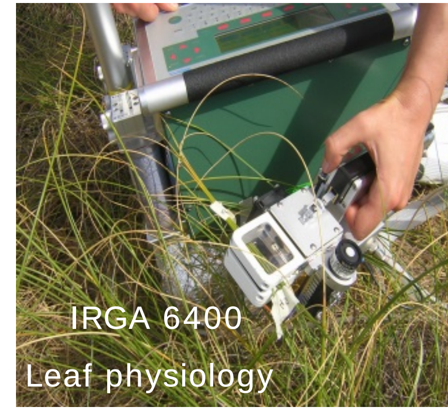
Gillespie, 2014

Relation between spectral indices and plant physiology: much less explored

Annual precipitation : 370mm

Correlations between canopy spectral indices and leaf physiology?

*$p<0.05$, $p<0.01$



Indicator	Spectral index (bands)	Photosynthesis (μmol CO_2 m^{-2} s^{-1})	Light Use Efficiency (g C MJ−1)	Transpiration (mm/s)	Conductance (m/s)
Green vegetation (LAI, fPAR)	Normalized Difference Vegetation Index NDVI (800, 670)	0.65	0.56	0.48	0.07
Canopy water content	Normalized Difference Water Index NDWI (860, 1240)	0.86*	0.66	0.87*	0.30
Xanthophyll cycle	Photochemical Reflectance Index PRI (570, 531)	0.12	0.28	-0.42	-0.94**
Chlorophyll content	(750, R710)	0.95**	0.88*	0.68	-0.09
Carotenoids content	(800, 470)	0.96**	0.84*	0.81	0.09
Water stress	Tcanopy − Tair (thermal)	−0.90*	−0.83	0.88*	-0.64
Water stress	Tsoil − Tcanopy (thermal)	−0.93*	−0.83	0.93*	-0.80

Agricultural Water Innovations in the Tropics (AgWIT)

Motivation: Water and carbon footprints of tropical crops exported to EU

Increase crop water use efficiency

Testing new strategies

Biochar additions under rainfall and rainfed crops. Agricultural impacts on water resources?

Evaluate soil and water management strategies via ecophysiological assessments of crops and quality of soil leachate

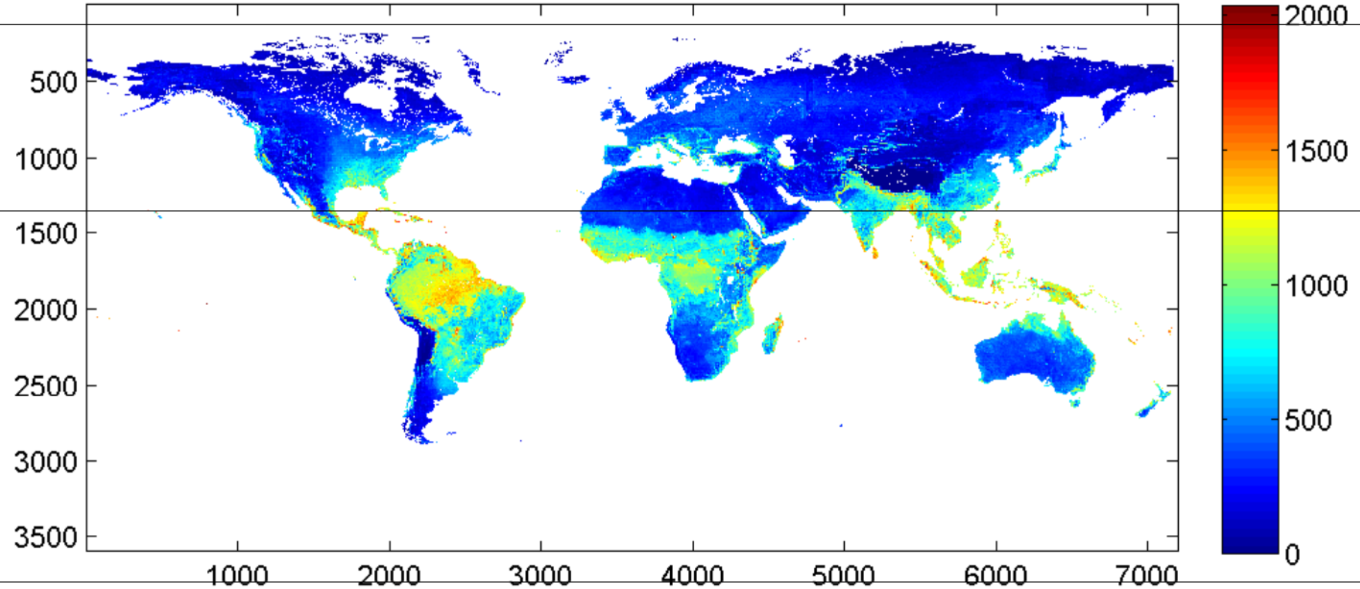
Prototype Global ET based on Sentinel-3

✓ Four different **operational** approaches tested and merged

✓ Minimum climatic inputs and optimization with field datasets

$ET_{PT\text{-}JPL}$ **ET_{TSEB}** **ET_{STIC}** **ET_{MP}**

ET ensamble



Average annual ET (mm) condition from 2009 to 2012

Mallick et al., 2015

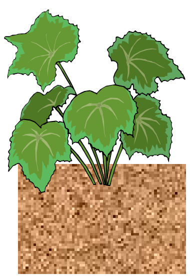
$ET_{PT\text{-}JPL}$ evapotranspiration model

- Evolutionary assumption: ecosystems optimize carbon fixation/water losses by scaling canopy leaf area and light harvesting to the availability of resources. (Nemani & Running, 1989, Eagleson, 1986).
- Neglects behavior of individual leaves -> canopy bulk response
- Best among 4 global models. Deficiencies during conditions of water stress (Miralles et al., 2016).

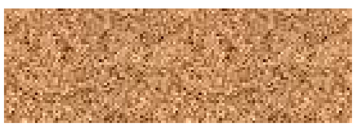
Net radiation (Rn) partitioned based on vegetation cover

(Beer Lambert law)

Canopy: *c*



Bare soil: *s*



PT-JPL

$$\lambda E_c = f_g \cdot f_T \cdot f_M \cdot \lambda E_{c\_potential}$$

$$\lambda E_s = f_{SM} \cdot \lambda E_{s\_potential}$$

Solves evapotranspiration λE

Plant constraints limiting transpiration

Soil moisture constraint limiting evaporation

Garcia et al., RSE 2013

$ET_{PT\text{-}JPL}$ evapotranspiration model

✓Proof of concept: Effect of soil moisture estimates into $ET_{PT\text{-}JPL}$ algorithm under extreme conditions (mean ET< 1 mm/day)

✓Soil moisture controls stomatal and soil conductance to vapor.

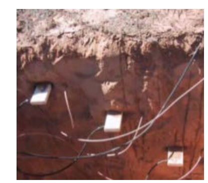
Complementary hypothesis:

land-atmospheric coupling.Meteo data

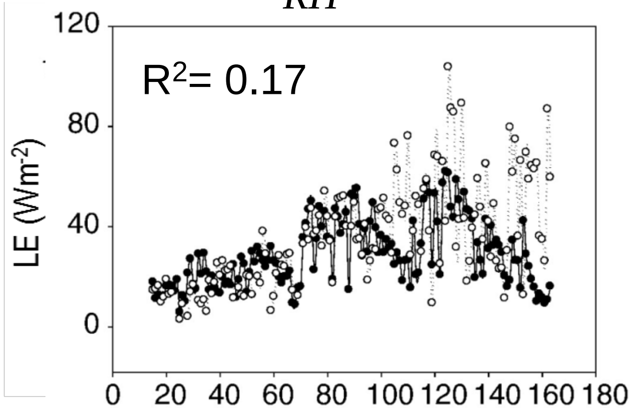
Thermal inertia

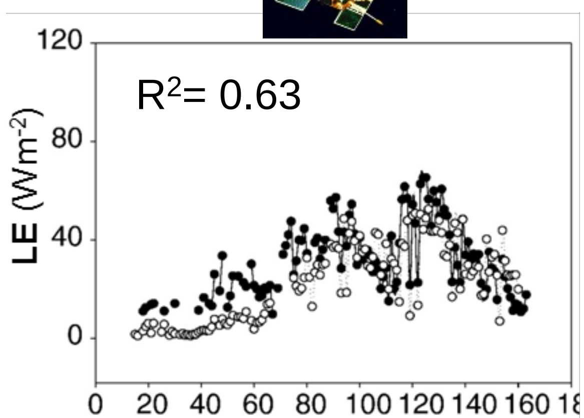
LST, albedo from Meteosat SEVIRI

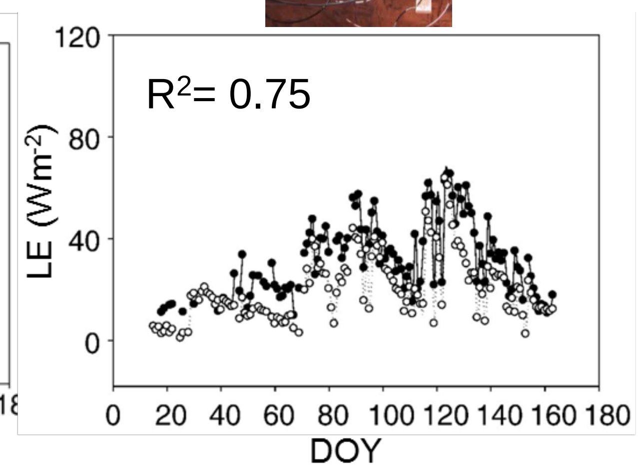
Field measured soil moisture (TDR)



$RH^{VPD/\beta}$





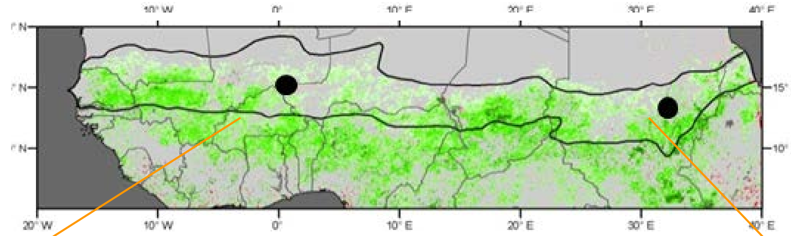


Flux tower: 20% uncertainty (black dots)

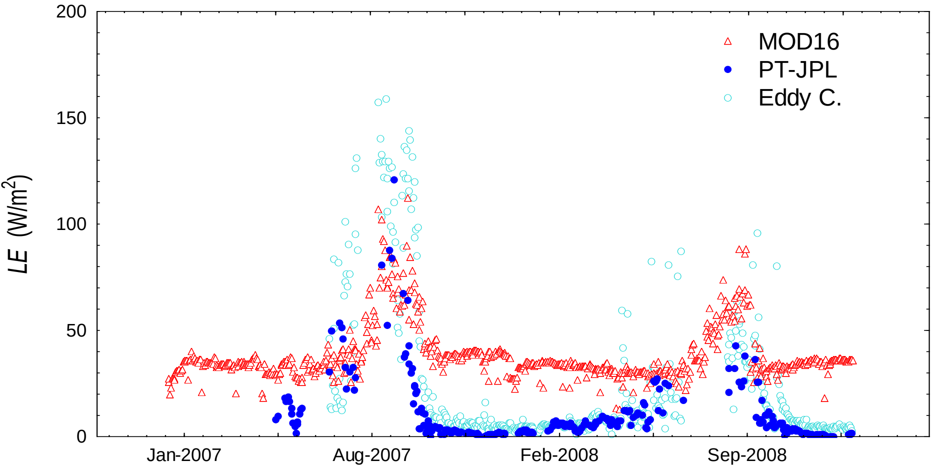
Garcia et al. (2013)

$ET_{PT\text{-}JPL}$ evapotranspiration model

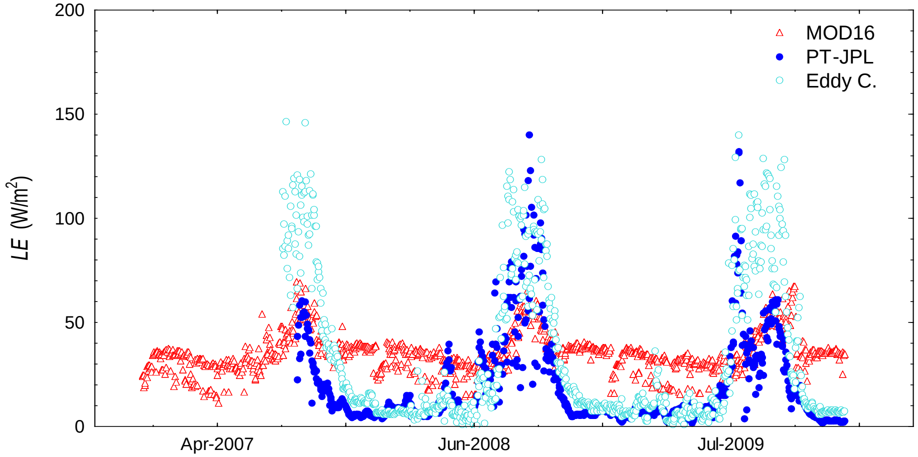
- ✓ Proof of concept: $ET_{PT\text{-}JPL}$ algorithm at extreme environment Sahel



Agoufou (Mali)



Demokeya (Sudan)



Algorithm	n	MAE W/m^2	bias W/m^2	r
MOD16	488	27.11	-15.39	0.70
PT-JPL	276	11.53	9.55	0.75

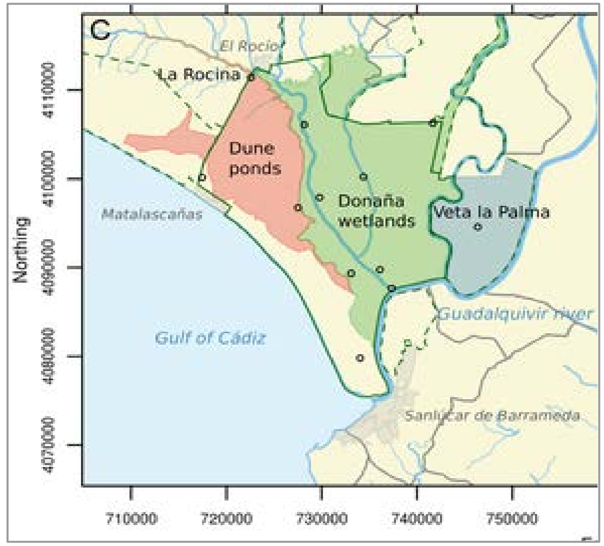
Algorithm	n	MAE W/m^2	bias W/m^2	r
MOD16	877	26.72	3.41	0.60
PT-JPL	837	15.80	-11.87	0.79

Garcia et al., in prep.

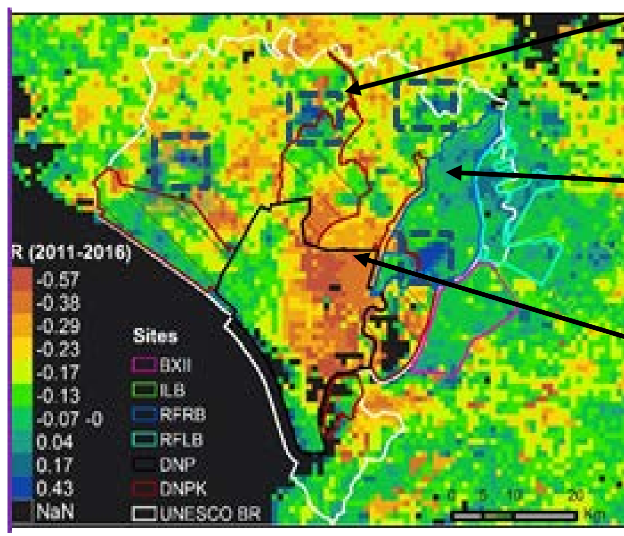
Wetland degradation? Water use from crops and ecosystems

Doñana Natural Area:
Biosphere Reserve

Morris et al.,2013



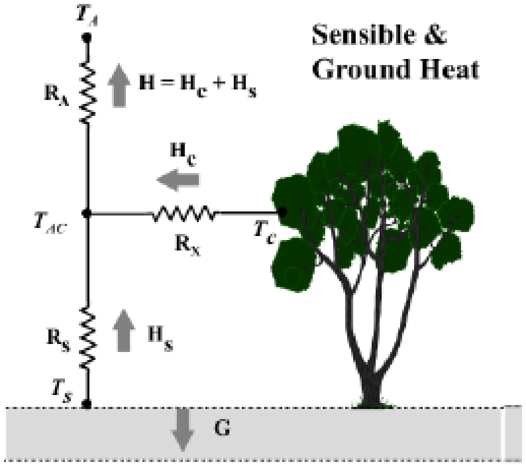
Temporal trends in evapotranspiration



✓ Quantified an increasing trend in water use in new berry fields and decreasing in wetland: Hotspots

Moyano et al., in prep

ET_{TSEB} evapotranspiration model

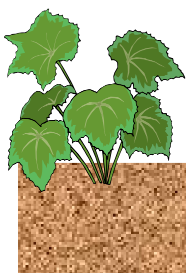


Assumption: flux gradient theory for calculating sensible heat flux based on radiometric temperature for soil and for vegetation.

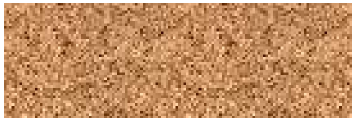
Net radiation (Rn) partitioned based on vegetation cover

(Beer Lambert law)

Canopy: *c*



Bare soil: *s*



$$H_c = \rho C_P \frac{T_c - T_a}{r_{AH}}$$

$$H_s = \rho C_P \frac{T_s - T_a}{r_{AH} + r_s}$$

TSEB

$$\lambda E_c = Rn_c - H_c$$

$$\lambda E_s = Rn_s - H_s - G$$

Solves Sensible heat flux *H*

Canopy radiometric temperature

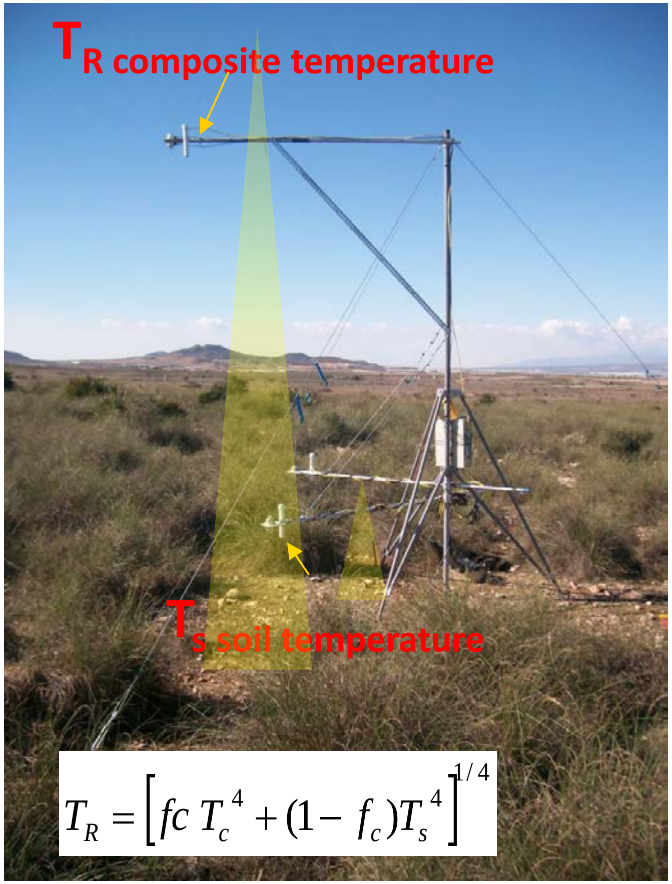
Soil radiometric temperature

Morillas et al., RSE 2013

ET_{TSEB} evapotranspiration model

Motivation

- ✓ Test the model in dryland sparse vegetation conditions (series and parallel)
- ✓ Evaluate the algorithm to separate temperature into soil and vegetation



Temperature Unmixing

Numerical approach

T_R (composite)

T_c (vegetation) ← T_R → T_s (soil)

Input of separate temperatures

T_c (vegetation) T_s (soil)

	H	λE
R^2	0.75-0.80	0.36-0.39
MAPE%	25-33	74-95

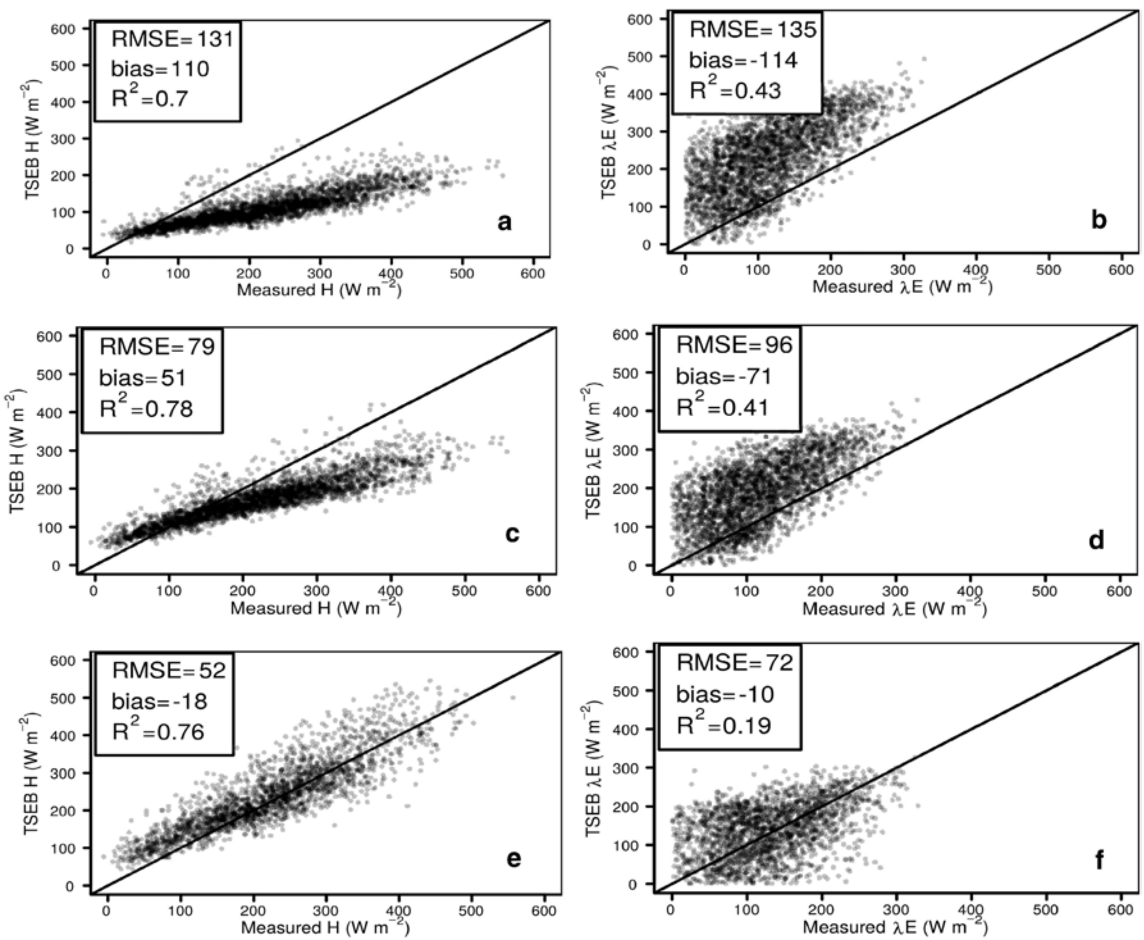
Robust procedure: minor differences in outputs

ET_{TSEB} evapotranspiration model

Accurately quantifying interaction in drylands of soil and vegetation in partially or sparsed vegetated areas remains challenging (Haghighi et al 2017, WRR).

Sensible heat

Latent heat



TSEB standard algorithm

MODIS LAI

TSEB standard algorithm

LAI from field

TSEB with modified aerodynamic resistances

Kustas et al., 2016

Gross Primary production (GPP) model

- ✓ Atmospheric CO_2 absorbed by terrestrial ecosystems through photosynthesis. Largest carbon flux between land and atmosphere.
- ✓ Light use efficiency concept is based on **Functional convergence theory:** **“**Plants scale canopy leaf area and light harvesting by the availability of resources as a result of evolutionary processes in order to optimize their carbon fixation”

(Field et al., 1991; Goetz & Prince, 1999)

Light use efficiency · *Fraction of absorbed PAR* · *PAR radiation*

$$GPP = \varepsilon \;\; f_{PAR} \cdot PAR$$

Biophysical constraints limiting transpiration and assimilation

$$GPP = \varepsilon_{max} \cdot f_{VPD} \cdot f_T \cdot f_{SM} \cdot f_{PAR} \cdot PAR$$

Max light use efficiency

Monteith et al., (1977)



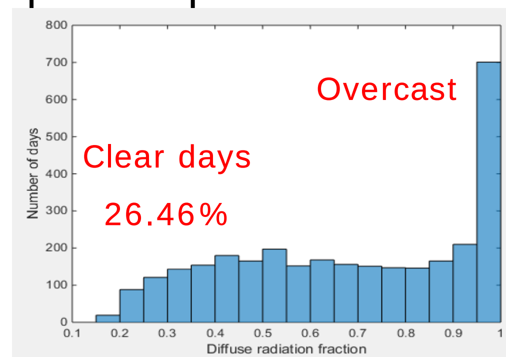
Model development and testing

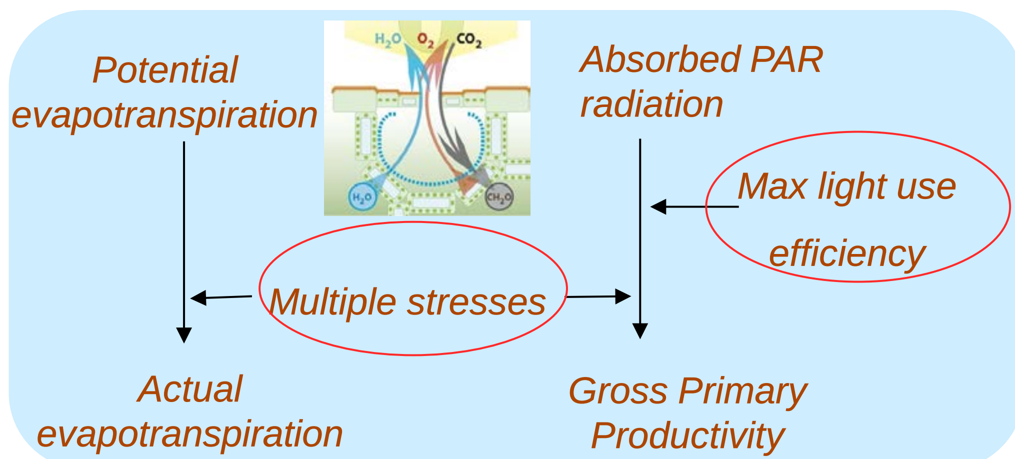
Motivation

- ✓ Remote sensing based models of evapotranspiration and gross primary productivity biased to clear sky conditions
- ✓ Include and quantify effect of diffuse radiation (Clouds, aerosols)
- ✓ Assume the biophysical constraints for evapotranspiration same as for GPP

Sorø flux site

11 years of data!





Wang, et al., 2017, AFM.

Light use efficiency model used to understand effects of diffuse radiation

✓ Model including effects of diffuse and direct radiation improved estimates

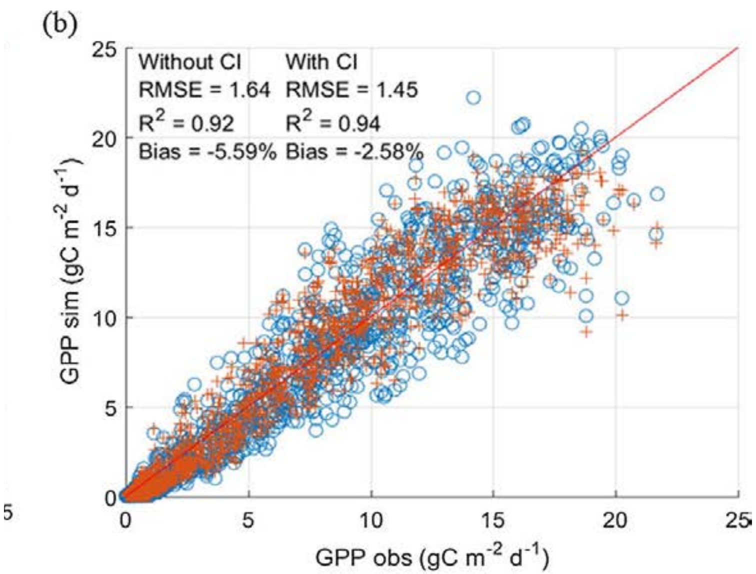
Data Driven

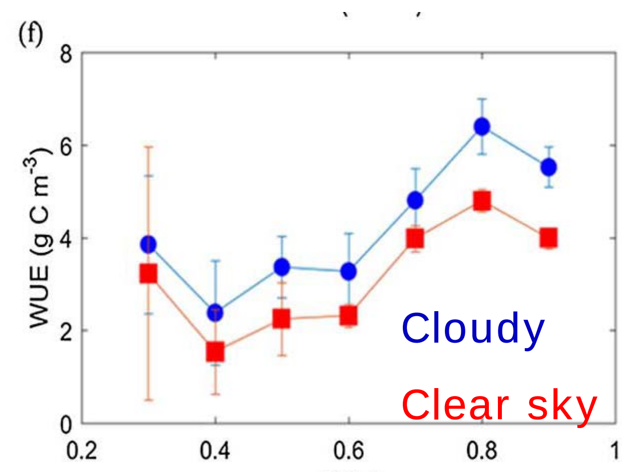
Path analysis

→ ***Quantify*** effect of diffuse radiation ←

Model

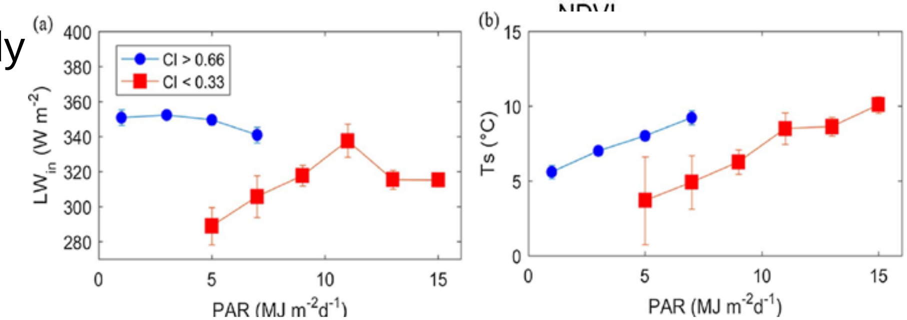
Global sensitivity analysis





✓ Higher Water Use Efficiency with cloudy conditions

✓ Warming effect from clouds increasing canopy temperature (Ts) (NDVI>0.75)



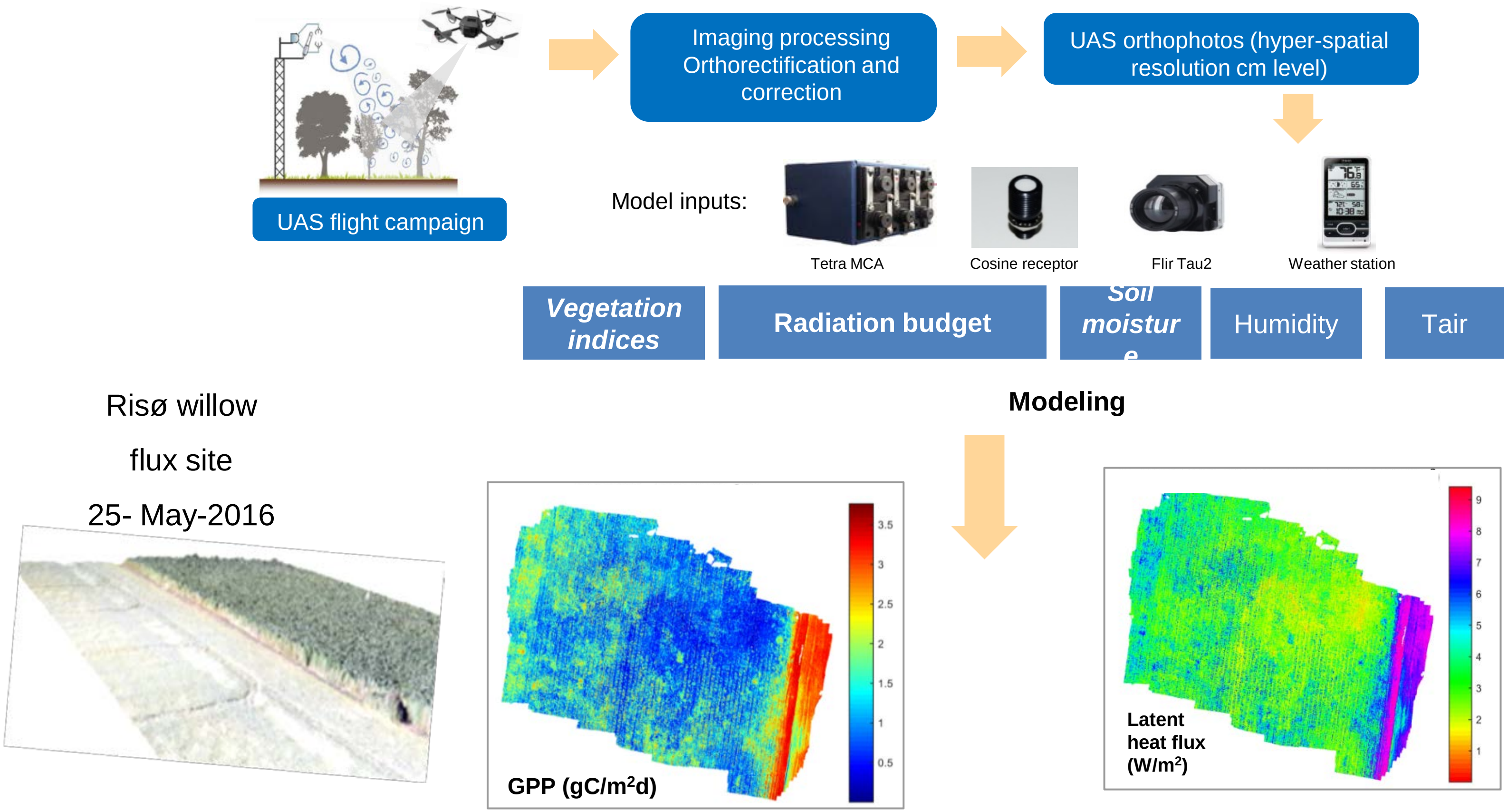
Wang, et al., 2017, AFM.

DTU high resolution mapping system for ET and GPP

Motivation:

✓Operational estimates of daily GPP and ET from UAV

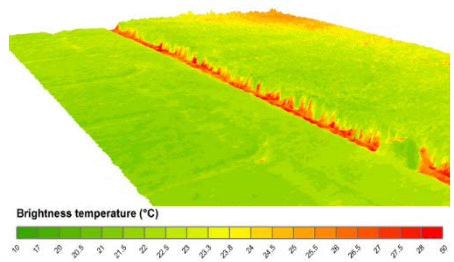
✓ Needed for detailed (submeter) water and carbon footprints, crop yields, biomass, water resources.

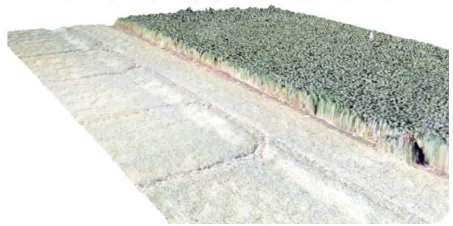


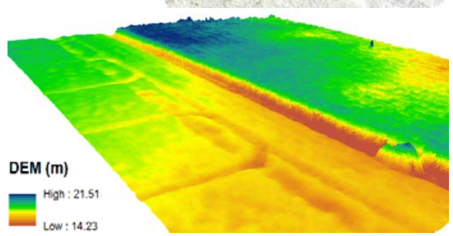
Sheng et al, 2016

Soil moisture using thermal UAV data: TVDI

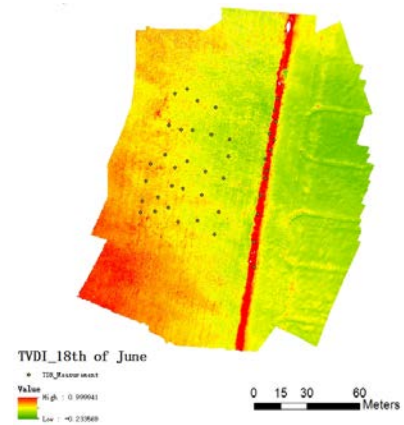
Challenge: geometric and accurate radiometric corrections: <2 K and < 20 cm



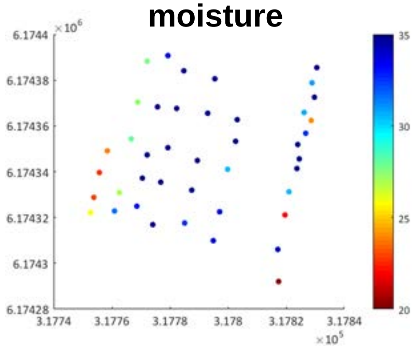


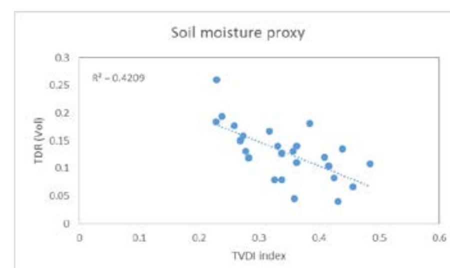


Soil moisture index



Portable TDR: soil moisture



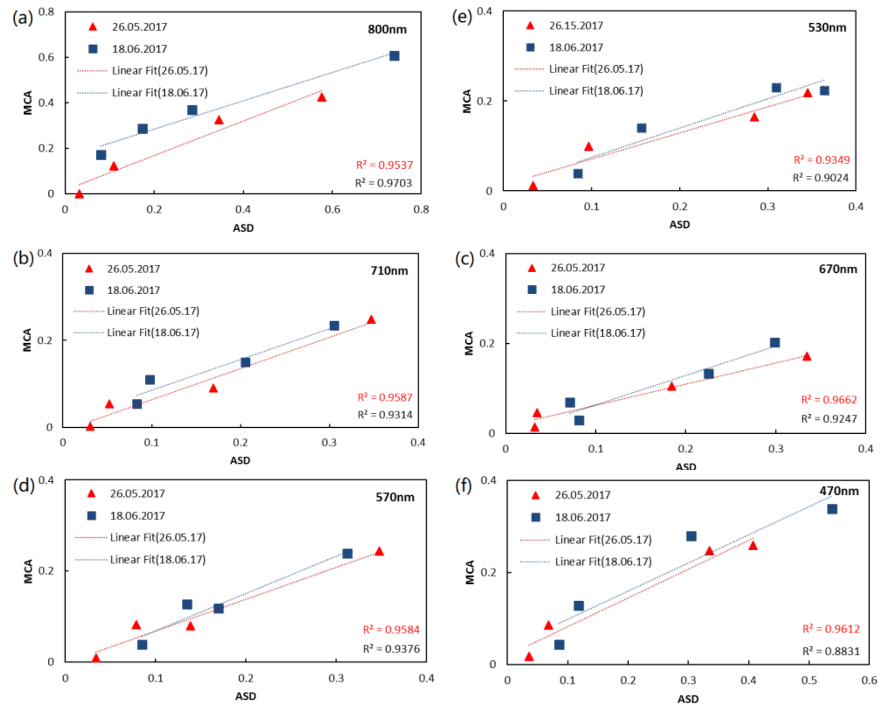


Liu et al., in prep.

UAS imagery validation

- MCA reflectance validation (ASD)

Four colors of tarpaulins



Payload: calibrations of multispectral camera

Low illumination conditions.

- Geometric calibration: retrieve intrinsic camera geometric parameters

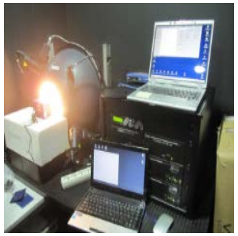
  To improve the accuracy of image mosaicking

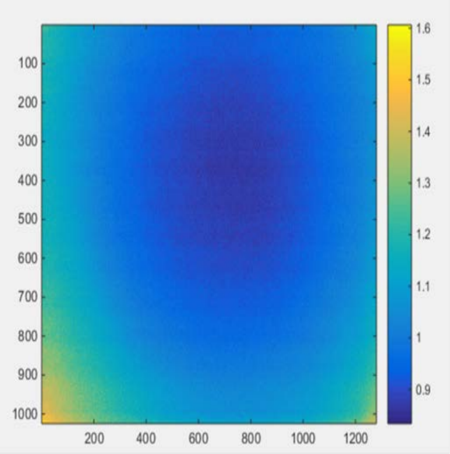
- Vignetting correction: homogenous illumination from the sphere

  To reduce the radiometric distortion

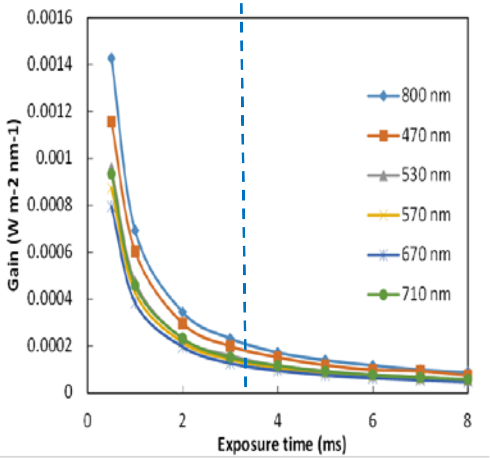
- Radiometric calibration: Converting digital number (DN) to radiance (L)

  Extended calibration for low illumination conditions (exposure time):





Vignetting Correction factors (to the mean value)

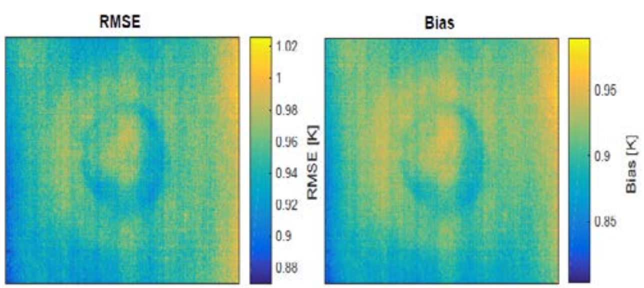


The faction of gain for six channels

Payload: the thermal infrared camera

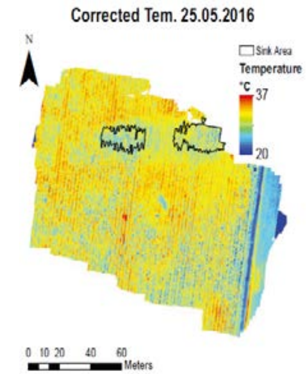
Flir Tau 324 (7.5-13.5 µm)

- To retrieve the **land surface temperature**
- Pixel wise calibration with a black body (emissivity =1)



The accuracy of pixel-wise calibration for each pixel (RMSE and bias)

- Example of corrected temperature orthophoto
- Place: Risø willow flux site, DK
- Time: 25-May-2016 11:15 a.m.
- Flying altitude: 80m



- Correction for the surface emissivity and the atmospheric effects

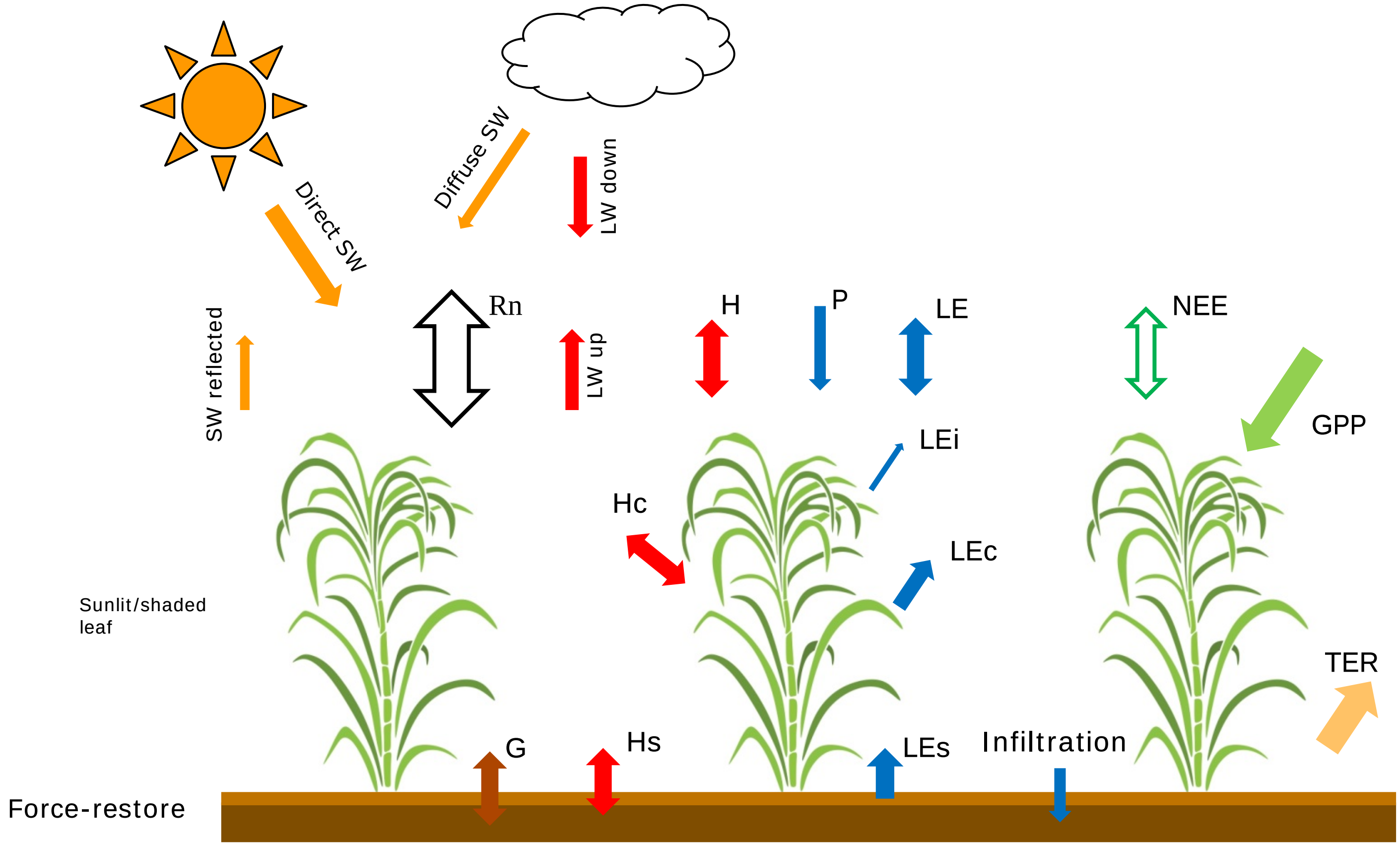
$$L_\lambda(\theta) = \tau_\lambda(\theta)\left[\varepsilon_\lambda B_\lambda(LST) + (1-\varepsilon_\lambda)\frac{L_\lambda^{\downarrow}}{\pi}\right] + L_\lambda^{\uparrow}(\theta)$$

- $\tau_\lambda(\theta)$: Atmospheric transmisivity (H_2O+other gases)
- $\varepsilon_\lambda B_\lambda(LST)$: Emitted radiance by the surface
- $(1-\varepsilon_\lambda)\frac{L_\lambda^{\downarrow}}{\pi}$: Atmospheric irradiance (downwelling path) reflected by the surface
- $L_\lambda^{\uparrow}(\theta)$: Atmospheric irradiance (Upwelling path)

How to interpolate ET and GPP between flights?

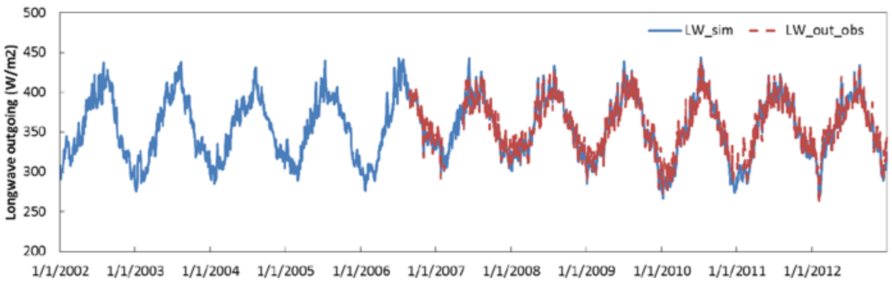
Motivation:

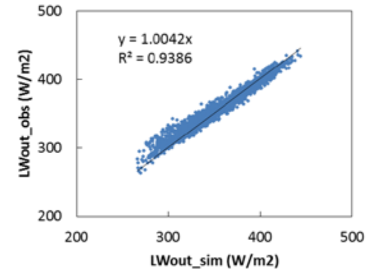
- ✓ Operational Model ET and GPP between flights: ”Smart interpolator”
  - ✓ Soil-vegetation-atmosphere transfer (SVAT) model: exchanges of energy, water vapor, and momentum across soil–vegetation–atmosphere continuum.



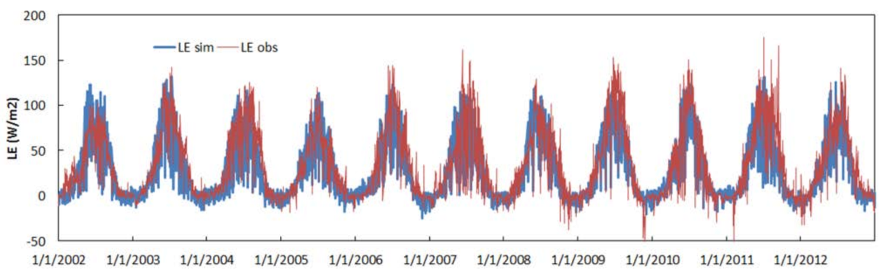
Dynamic model of ET and GPP between observations

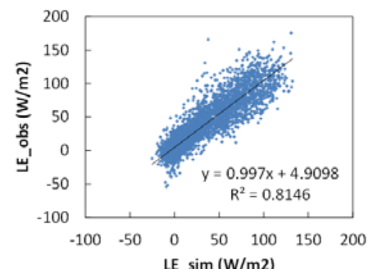
At Soroe beech forest



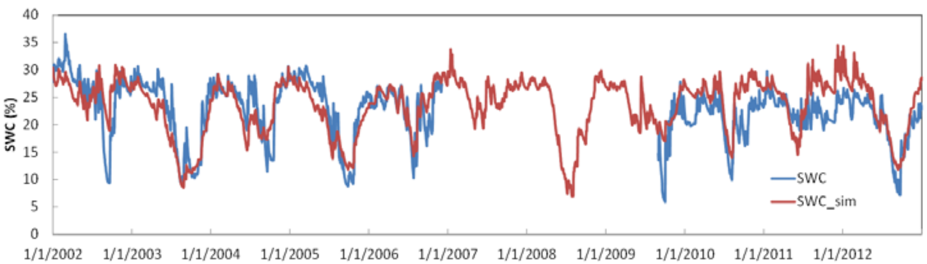


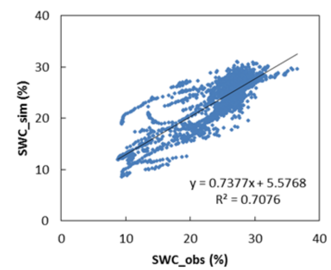
Longwave outgoing radiation



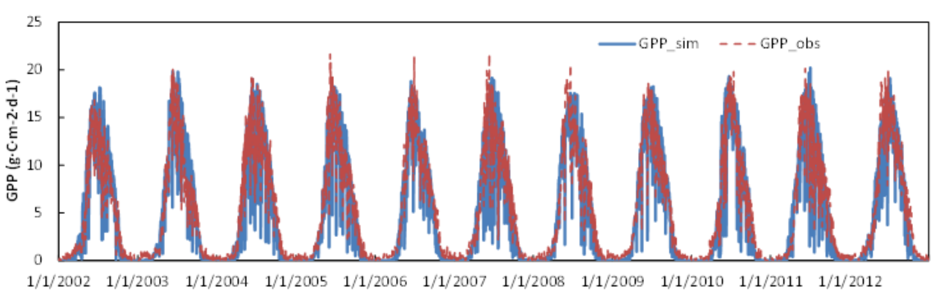


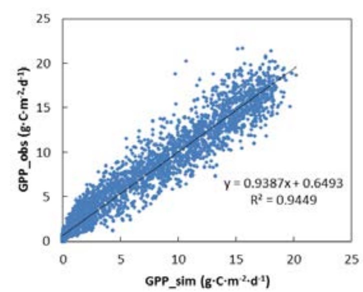
Latent heat flux





Soil moisture





Gross Primary Productivity

Summary

- Land surface process are linked: we cannot understand and predict the hydrological cycle components in isolation but in relation to other land surface processes related with the energy and carbon cycles
- Different types of remote sensing data provide information on the reflectance and emission of light in different wavelenghts→ useful to estimate energy budgets and vegetation status.
- “Top down” models of evapotranspiration and GPP can incorporate remote sensing data with minimal calibrations or parameterization. Challenges in drylands with no irrigation.
- UAV platforms are flexible and provide very high spatial/spectral resolution. The challenge is to provide consistent time series of state variables
- To account for gaps between remote sensing acquisitions (cloud cover, revisiting time) we propose to use simple Soil Vegetation Atmosphere Transfer Scheme forced with climatic data.

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